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COMMUTING FOR CRIME*

Tom Kirchmaier, Monica Langella and Alan Manning

People care about crime, with the spatial distribution of both actual and perceived crime affecting the local amenities from living in different areas and residential decisions. The literature finds that crime tends to happen close to the offender's residence, but does not clearly establish whether this is because the location of likely offenders and crime opportunities are close to each other, whether more local crimes are likely to be solved or whether there is a high commuting cost for criminals. We use a rich administrative dataset from one of the biggest UK police forces to disentangle these hypotheses, proposing a procedure for controlling for the selection bias induced by the fact that an offender's location is only known when they are caught. We find that the cost of distance is very high, especially for crimes without any financial gain. For property crimes, we find a similar cost of distance to commuting for legal work. We also investigate how local socio-economic characteristics affect both the number of criminals and the number of crimes.

Fear of crime and actual crime rates matter to people. There is evidence that crime rates have an important influence on economic decisions, e.g., consumption decisions (Mejia and Restrepo, 2016), house prices (Gibbons, 2004), the type of economic activity in the area (Rosenthal and Ross, 2010) and satisfaction with the area (Langella and Manning, 2019). Political campaigns often focus on crime and crime prevention, and this topic is very relevant in the public debate.

Crime rates[1] vary greatly across areas, being typically higher in cities than in rural areas and, within cities, higher in the inner city than the suburbs (Glaeser and Sacerdote, 1999; Zenou, 2003; Verdier and Zenou, 2004; Almeida da Matta and Viegas Andrade, 2011; Gaigne and Zenou, 2015). These differences are very persistent (Glaeser *et al.*, 1996).

This paper uses administrative data from the Greater Manchester Police (GMP) on all crimes recorded between April 2008 and March 2018 (see also Khanna *et al*. (2022) for similar data for Colombia). The GMP area covers a population of 2.6 million, making it one of the biggest police forces in the UK in terms of population.

We investigate the spatial distribution of crimes and of the people who commit them. Specifically, we model the number of crimes committed in every neighbourhood by residents of every

* Corresponding author: Alan Manning, Centre for Economic Performance, London School of Economics, Houghton Street, London WC2A 2AE, UK. Email: a.manning@lse.ac.uk

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The authors were granted an exemption to publish their data because access to the data is restricted. However, the authors provided a simulated or synthetic dataset that allowed the Journal to run their codes. The synthetic/simulated data and codes are available on the Journal repository. They were checked for their ability to generate all tables and figures in the paper; however, the synthetic/simulated data are not designed to reproduce the same results. The replication package for this paper is available at the following address: https://doi.org/10.5281/zenodo.10013351.

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[1] We refer to crime rates as crimes per 1,000 population. Similarly, offenders' rates are the number of offenders per 1,000 population.

other neighbourhood as a function of the distance between them, as well as of crime and offender location fixed effects.

Not all crimes are solved, and the sample of crimes with a known offender may not be a random sample of all crimes. The selection problem is acknowledged by the existing literature,[2] but, as far as we know, this is the first paper to control for it. It is important to adjust for this source of selection as it is most likely non-random and a potential cause of bias. For instance, the extent to which crime is local will be mismeasured if the probability of solving a crime—i.e., matching an offender to a crime—is correlated with distance, which is likely to be the case. We show how an instrument that affects the probability of a crime being solved, but not the number of crimes in the area can be used in a control function setting to include a selection bias correction in our estimated equations. The instrument we use is the response time of the police to the crime. Response time has great variability and has been shown to affect the probability of solving the crime (Blanes i Vidal and Kirchmaier, 2018), though, we argue, is unlikely to have a direct effect on the location of the crime and the location of the offender, conditional on the controls we include in the model.

Our approach offers several advantages relative to the existing 'journey-to-crime' (JtC) literature that started in the 1920s (Park and Burgess, 1925; Lind, 1930; White, 1932).[3] This literature finds that most crime is short distance, which is also true in our data as we find that the average car time distance[4] is about ten minutes. A limitation of this literature is that it does not address why JtCs are short. It could be, for instance, that crimes with shorter distances are more likely to be solved; our correction for selection bias deals with this. Alternatively, it could be that lucrative targets tend to be close to the offender's home, i.e., the locations of criminals and criminal opportunities are positively spatially correlated. Our inclusion of origin and destination fixed effects controls for this. Areas with high origin fixed effects can be interpreted as areas with a relatively high number of offenders, while areas with high destination fixed effects are areas where the number of crimes committed is higher.

Our main conclusions are that controlling for selection is important, and not taking it into account leads to an overestimate of the 'cost of distance', pointing to the fact that offenders are more likely to be found if they live closer to the crime location. We also find that the origin and destination fixed effects are positively spatially correlated, so criminals and criminal opportunities tend to be located together. However, the cost of distance remains very high and crime a very local phenomenon. Increasing distance by just ten minutes of car time reduces the probability of committing a crime in a given place by 92% for violent crimes, 83% for property crimes and 93% for other crimes. The estimated cost of distance for property crimes is similar to what we find estimating a model for commuting flows for (legal) work. We also find evidence that areas that are better connected through public transport tend to have higher crime links. Halving the ratio between public transport time and car time increases the probability of observing a crime by 36% for violent crimes, 16% for property crimes and 24% for other crimes.

We also model the origin and destination fixed effects obtained from the distance model as functions of the characteristics of these areas, such as the age composition, industrial structure

[2] Thaler (1977) discussed how a state-level analysis is not likely to capture the local dimension of crime and found a negative relation between the probability of being arrested and travel time to commit a crime. Deutsch *et al.* (1987) provided a model to explain crime location dynamics and how they change with age. Deutsch and Epstein (1998) constructed a model to explain clustering of criminal activities and showed that spillover effects to other areas are likely to be driven by police activity.

[3] See Ackerman and Rossmo (2015) for a thorough review of the criminology literature on this topic.

[4] We analyse and compare different measures of distance.

and deprivation. A regression of area-of-origin fixed effects on area characteristics will tell us about how the local socio-economic structure affects the presence of offenders. Similarly, a regression where the area-of-destination fixed effects are used as the dependent variable will tell us about how the local socio-economic structure affects the incidence of crimes.

Since the seminal work of Becker (1968), empirical research in the economics of crime has focused on factors that affect the returns to crimes, such as employment rates (Zenou, 2003; Verdier and Zenou, 2004; Gaigne and Zenou, 2015) or unemployment (Cantor and Land, 1985; Freeman, 1999; Raphael and Winter-Ebmer, 2001; Gould *et al.*, 2002; Lin, 2008; Buonanno *et al.*, 2014; Bender and Theodossiou, 2016; Hémet, 2020), job opportunities (Engelhardt, 2010; Bell *et al.*, 2018), wage levels (Entorf and Spengler, 2000; Gould *et al.*, 2002; Machin and Meghir, 2004) and crime revenues (Draca and Machin, 2015; Draca *et al.*, 2019).[5] One of the issues in estimating the impact of economic conditions on crime is that it is hard to disentangle changes in the return to crime from changes in the opportunity cost of crime. For instance, those in poorer areas with worse job opportunities may have greater incentive to become a criminal, but there might be ‘less to steal’, so the returns to crime might be lower (Kang, 2016). Our approach distinguishes these two effects as we separately estimate fixed effects on the offenders’ side[6] and on the crime location side. Khanna *et al.* (2022) sought to model the spatial work and crime decisions simultaneously, considering the impact of improvements to the transport network.

We find that unemployment has a positive relationship with both offender and crime location fixed effects. A higher share of graduates is associated with fewer offenders for all types of crime, but has no significant relation with the incidence of crimes. A higher number of businesses in an area is associated with fewer offenders, but more crimes.

The plan of the paper is as follows. Section 1 describes the dataset; Section 2 discusses the model for the location of crimes and our procedure for dealing with the selection bias. Section 3 illustrates the empirical estimates and presents the results for both the distance function and the fixed effect estimates. Section 4 provides some extensions to our main cost of distance analysis, and Section 5 concludes.

1. Data

We use administrative data from the Greater Manchester Police on all crimes handled by GMP between April 2008 and March 2018. GMP is one of the biggest police forces in the UK, with approximately 6,200 police officers (Blanes i Vidal and Kirchmaier, 2018), covering an area with a population of approximately 2.6 million people, 12% of the total population in England and Wales. Table A1 in the Online Appendix compares the demographic characteristics[7] of the GMP area with England and Wales as a whole. The GMP area is slightly younger, has a higher proportion of students and lower proportions of migrants and white people. The proportion of

[5] Revenues and job opportunities are not the only aspects named as potential drivers of criminal activities. Among others, the literature has focused on risk attitudes and specialisation in criminal activities (Ehrlich, 1973; 1996; Viscusi, 1986); the probability of punishment, both actual (Fisman and Miguel, 2007; Buonanno *et al.*, 2011; DeAngelo, 2012; Bell *et al.*, 2014; Chalfin and McCrary, 2017; Doleac, 2017) and perceived (Lochner, 2007); the probability of incarceration (Barbarino and Mastrobuoni, 2014); the diffusion of self-protection tools as security systems (Vollaard and Van Ours, 2011).

[6] It may be that the impact of the local economic conditions varies with offender characteristics, e.g., young men seem in general more sensitive to economic conditions (Grogger, 1998; Fougère *et al.*, 2009; Grönqvist, 2011).

[7] From the 2011 Census of Population (source: Nomis, https://www.nomisweb.co.uk/sources/census_2011).

people with a university degree is lower than the average of the country, while the unemployment rate is higher. Fewer people are married or in a stable couple.

1.1. *Crimes*

The police initially record all cases received as incidents; a subset is then assessed to be criminal activities and coded as crimes. This paper focuses only on incidents classed as crimes. We exclude domestic abuse crimes as they tend to be perpetrated inside the house, so journey to crime is necessarily zero.[8] We also exclude frauds as their definition and codification has changed over time. Cybercrimes are also excluded as they raise different spatial considerations, and we are interested in more 'traditional' types of crime where the offender needs to be physically present at the crime location. After these restrictions, the dataset contains information on over two million crimes. There are some crimes that are not recorded by the police either because the victim may be unaware (e.g., undetected shoplifting) or there is no victim (e.g., carrying a weapon that is not used or purchase of an illegal drug). Absent any information on the number of unrecorded crimes, we cannot address the selection from actual to recorded crimes.

The data set records information on the type of crime. Figure 1(a) illustrates the distribution of recorded crimes by type;[9] burglaries and criminal damage are the most common. In our main analysis, we group crimes into three broad types—violent, property and other crimes.[10] Figure 1(b) shows how the level of crime varied over our sample period; violent and other crimes initially fell slightly, but increased after 2013/2014. Property crimes are more stable.[11]

Using the information on the location of the crime, we assign each offence to one of the 214 Census Area Statistics (CAS) wards in the Greater Manchester area, the measure of neighbourhoods we use.[12]

The dataset also contains detailed administrative information on who reported the crime and how, the degree of importance initially attributed to the crime by the call handlers (based on an assessment of vulnerability, threat and risk of harm) and the time it took the police to arrive at the scene. For 43% of crimes, police do not visit the scene, so response time is not available. For these crimes, we use the closing time of the case as recorded by the GMP police and include a dummy variable in the analysis to indicate these crimes. Descriptive statistics are reported in the first two columns of Table 1.

[8] Domestic abuse is a small proportion of the crimes and results are not sensitive to this exclusion.

[9] If a crime falls into multiple categories, the closing code of the crime will correspond to the most serious one, so there are no duplicates by crime identifier (Home Office, 2016). For the classification of crime types, we rely on the level-3 definition used by the police (https://www.justiceinspectorates.gov.uk/hmicfrs/media/crime-tree.pdf) illustrated in Figure A1 in the Online Appendix.

[10] We refer to the following level-3 categories as violent crime: homicide, violence with injury, violence without injury, other sexual offences and rape. As property crimes, we refer to robbery of business property, robbery of personal property, burglary, all other theft offences, vehicle offences, theft from the person, bicycle theft and shoplifting. As a remainder category, other types of crime will be criminal damage and arson offences, trafficking of drugs, possession of drugs, possession of weapon offences, miscellaneous crimes against society and public order offences. In general, drug use alone—in particular, 'low-risk' drugs—is not considered a crime and only drug possession and trafficking are included in the dataset. Possession of 'low-risk' drugs like cannabis or khat is also likely to be dealt with by the police in the form of a warning or on-the-spot fine (source: cps.gov.uk). Because of their mixed nature, robberies are sometimes defined as violent crimes and sometimes as property crimes. We follow the suggestion in Andresen *et al.* (2014) that highlights how crime location choice patterns, when robberies are considered, are more in line with property crimes rather than with violent crimes. The 19th type of crime in the Crime Tree Level-3 classification (Online Appendix Figure A1)—frauds—is also excluded from our study.

[11] These trends in the GMP area reflect wider England-wide trends, the reason for which is, but unclear.

[12] CAS wards are population-based areas designed for the 2001 census that accounted for, at the time of creation, approximately 5,000 people, so they are relatively small areas. They are comparable to US Census Tracts.

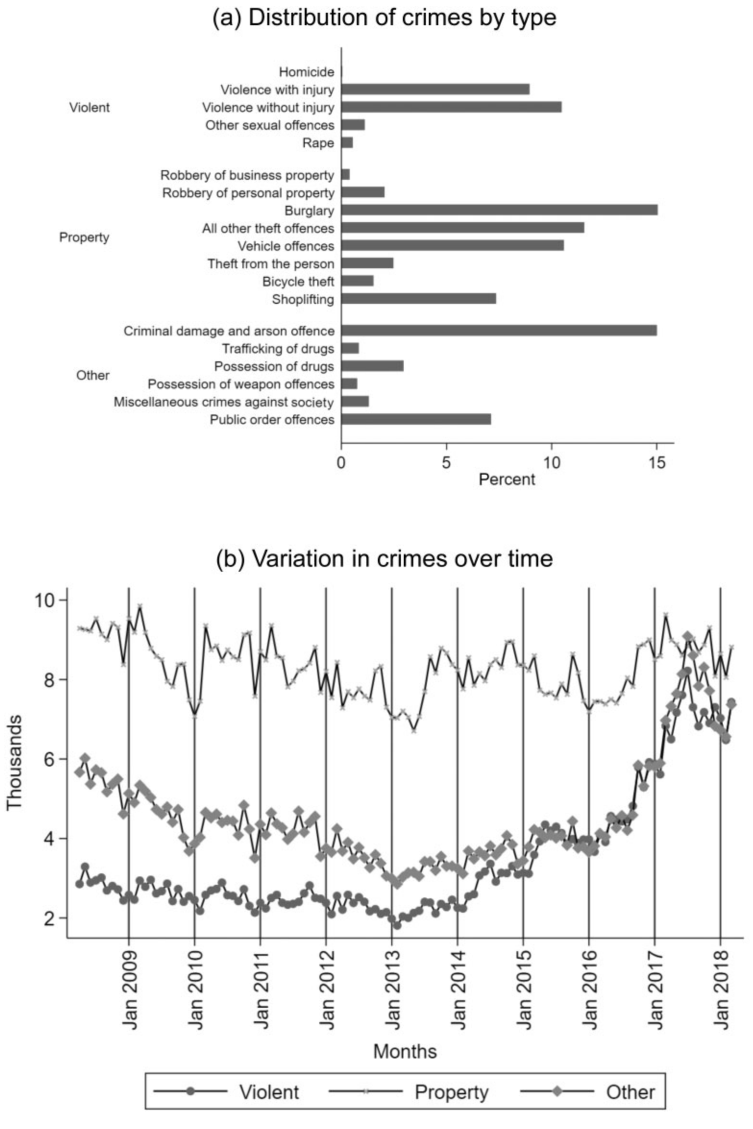

Fig. 1. *(a) Distribution of Crimes by Type. (b) Variation in Crimes over Time.*
Source: Authors' elaboration of GMP police force data. The crime categorisation follows the Crime Tree Level 3 illustrated in Figure A1 of the Online Appendix.

1.2. *Offenders*

Of crimes, 22.7% are solved, defined as finding at least one offender;[13] we refer to these as matched crimes. The final two columns of Table 1 show that the characteristics of matched crimes differ from those of unsolved crimes. Note that the response time is much lower, something we will use later. Figure 2(a) shows the matching rate (defined as the percentage of crimes that are matched)

[13] There may be multiple offenders for a crime; in the analysis we measure the distance to crime for each offender.

Table 1. *Crime Characteristics.*

	Panel A. All crimes		Panel B. Matched crimes	
	Mean	SD	Mean	SD
Response time (not imputed)	277.085	1,016.550	141.731	681.290
Response time: share imputed	0.444	0.497	0.149	0.356
Suspect named	0.209	0.407	0.448	0.497
Suspect described	0.193	0.395	0.127	0.333
Found by police	0.066	0.248	0.236	0.425
Found while patrolling	0.018	0.135	0.033	0.178
Reported by the victim	0.625	0.484	0.390	0.488
Type of crime:				
Homicide	0.0002	0.014	0.0006	0.025
Violence with injury	0.089	0.285	0.136	0.342
Violence without injury	0.105	0.306	0.135	0.342
Other sexual offences	0.011	0.105	0.011	0.104
Rape	0.005	0.073	0.005	0.067
Robbery of business property	0.004	0.062	0.004	0.063
Robbery of personal property	0.021	0.142	0.013	0.114
Burglary	0.150	0.357	0.060	0.238
All other theft offences	0.116	0.320	0.045	0.206
Vehicle offences	0.106	0.308	0.035	0.184
Theft from the person	0.025	0.155	0.004	0.060
Bicycle theft	0.015	0.122	0.003	0.058
Shoplifting	0.074	0.261	0.171	0.377
Criminal damage and arson offences	0.150	0.357	0.091	0.288
Trafficking of drugs	0.008	0.090	0.028	0.165
Possession of drugs	0.030	0.169	0.120	0.325
Possession of weapon offences	0.007	0.086	0.019	0.137
Miscellaneous crimes against society	0.013	0.113	0.021	0.144
Public order offences	0.071	0.257	0.099	0.298
Grade:				
Immediate	0.129	0.335	0.237	0.425
Priority	0.231	0.422	0.361	0.480
Prompt	0.173	0.378	0.221	0.415
Location:				
House	0.313	0.464	0.292	0.455
Shop	0.169	0.374	0.250	0.433
Other closed public/offices	0.082	0.275	0.076	0.265
Open air public	0.366	0.482	0.339	0.473
Transportation	0.013	0.111	0.009	0.099
Other	0.049	0.216	0.029	0.167
N/A	0.009	0.092	0.005	0.073
N	1,955,591		443,731	

Notes: Panel A includes descriptive statistics on the full sample of crimes. Panel B includes descriptive statistics on the sample of crimes matched to at least one offender. *Response time* is the time (in minutes) that elapsed between the creation of the case and the arrival of the police at the crime scene. If the arrival time is not available, we imputed the response time using the closing time instead of the time when the police arrive at the crime scene. *Response time: share imputed* reports the share of crimes in our sample for which we had to impute the response time. *Response time (not imputed)* reports the descriptive statistics for the response time in minutes before applying the imputation method. *Suspect named* is a dummy variable that takes value 1 if a suspect has been named by the victim or by some witnesses. *Suspect described* is a dummy variable that takes value 1 if a suspect has been described (not named) by the victim or by some witnesses. *Found by police* is a dummy variable that takes value 1 if the crime has been found directly by the police, *Found while patrolling* takes value 1 if the police found the crime during their patrolling activities and *Reported by the victim* takes value 1 if the victim reported the crime to the police. *Type of crime* is a set of dummy variables that indicate the crime categorisation (Crime Tree Level 3 illustrated in Figure A1 of the Online Appendix). *Grade* is a set of dummy variables indicating the priority of the crime as pre-determined by the police when opening the case. Different priority grades relate to different response time targets. *Location* is a set of dummy variables indicating the type of location where the crime was committed.

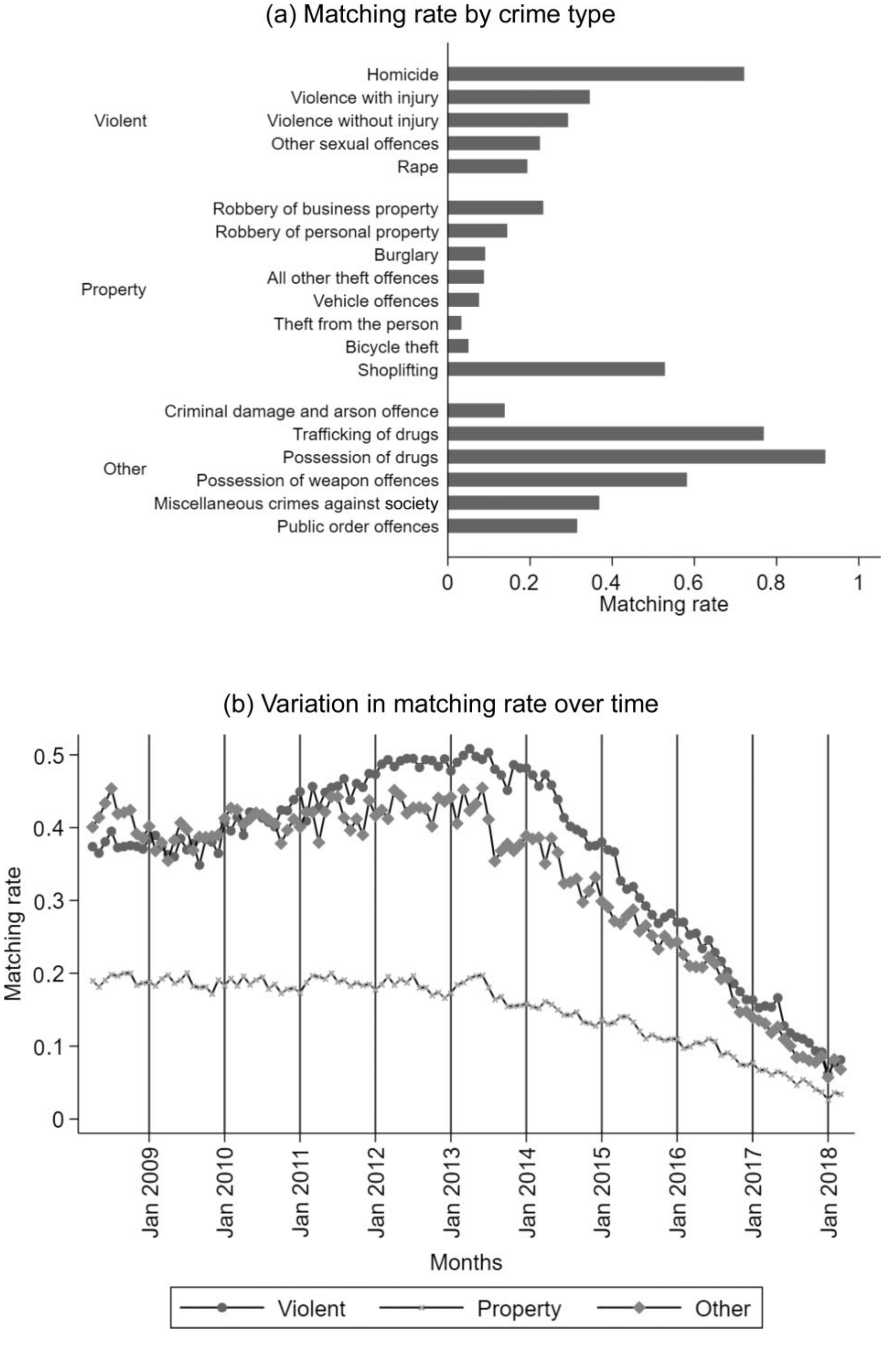

Fig. 2. *Matching Rates by (a) Matching Rate by Crime Type and (b) Variation in Matching Rate over Time* .
Source: Authors' elaboration of GMP police force data; monthly series. A matched crime is one for which at least one offender is found.

Table 2. *Offenders' Characteristics.*

	Panel A. All offenders		Panel B. First observed offence	
	Mean	SD	Mean	SD
Age at the time of the offence	27.85	11.81	28.73	12.97
% Women	18.67	38.97	24.05	42.74
% Chinese, Japanese or other South East Asian	0.16	4.04	0.29	5.42
% Other Asian	5.62	23.03	6.33	24.35
% Black	5.92	23.59	5.05	21.90
% Middle Eastern	0.41	6.40	0.50	7.07
% White—Northern European	72.71	44.55	64.11	47.97
% White—Southern European	1.01	9.98	1.05	10.19
% Unknown ethnicity	14.18	34.88	22.67	41.87
% UK national	74.62	43.52	62.33	48.46
N	401,770		169,964	

Notes: Panel A includes descriptive statistics on the full sample of matched crimes to offenders, with offenders having non-missing location information. Panel B includes descriptive statistics on the sample of unique offenders, so each offender is only recorded once. All variables are measured at the time of the offenders' first offences.

by type of crime. The matching rate is high for drug crimes and homicides, but very low for theft from the person. On average, property crimes have lower matching rates than violent crimes, except for shoplifting, which is frequently a 'caught in the act' crime. Figure 2(b) shows that the match rate for all types of crimes has fallen during the sample period.

The dataset records an address for the offender that we use to compute the journey to crime. In some cases, there is no address for the offender (e.g., they could be homeless) and we have to exclude these crimes. We exclude offenders—and the related crimes—who live outside the GMP area as well as GMP residents who commit crimes in other areas so that our study is of the number of crimes committed by GMP residents within the GMP area.[14] The final matched offender-crime dataset corresponds to approximately 362,000 individual crimes with 402,000 offenders in total. There are approximately 170,000 individual offenders, most having only one offence, but there is a long right tail.

Table 2 presents some descriptive statistics on offenders, both for all offenders (columns 1 and 2) and for their first offence (columns 3 and 4).[15] Offenders are quite young—28 years old on average, and only a minority of them—19%—are women. Offenders at their first offence are slightly older, suggesting that younger offenders may be more likely to commit multiple offences. In addition, women are a higher proportion of first-time offenders, so men re-offend more, as the share of women goes up for first-time offenders.

1.3. *The Spatial Distribution of Crimes and Offenders*

Crimes and offenders are distributed unequally across areas. Panel (a) of Figure 3 shows the spatial distribution of the number of crimes across wards per 1,000 population; crimes are more

[14] Of matched crimes, 5% have an offender from outside GMP. Crimes located outside GMP represent less than 1% of the whole crime sample. It may be viewed as a strong assumption to restrict the sample to the GMP area, though the alternative option would be to construct the dataset as a matrix that takes into account all possible ward-to-ward combinations in England, which could make the dataset size difficult to manage on the one side, while not including so much actual information on the other side, as the proportion of zeroes included by doing this would be extremely high. Though we stress that this could be a limitation, we still think that the trade-off goes in favour of treating the GMP area as a self-contained one.

[15] Table A2 in the Online Appendix also reports offenders' characteristics by detailed type of crime.

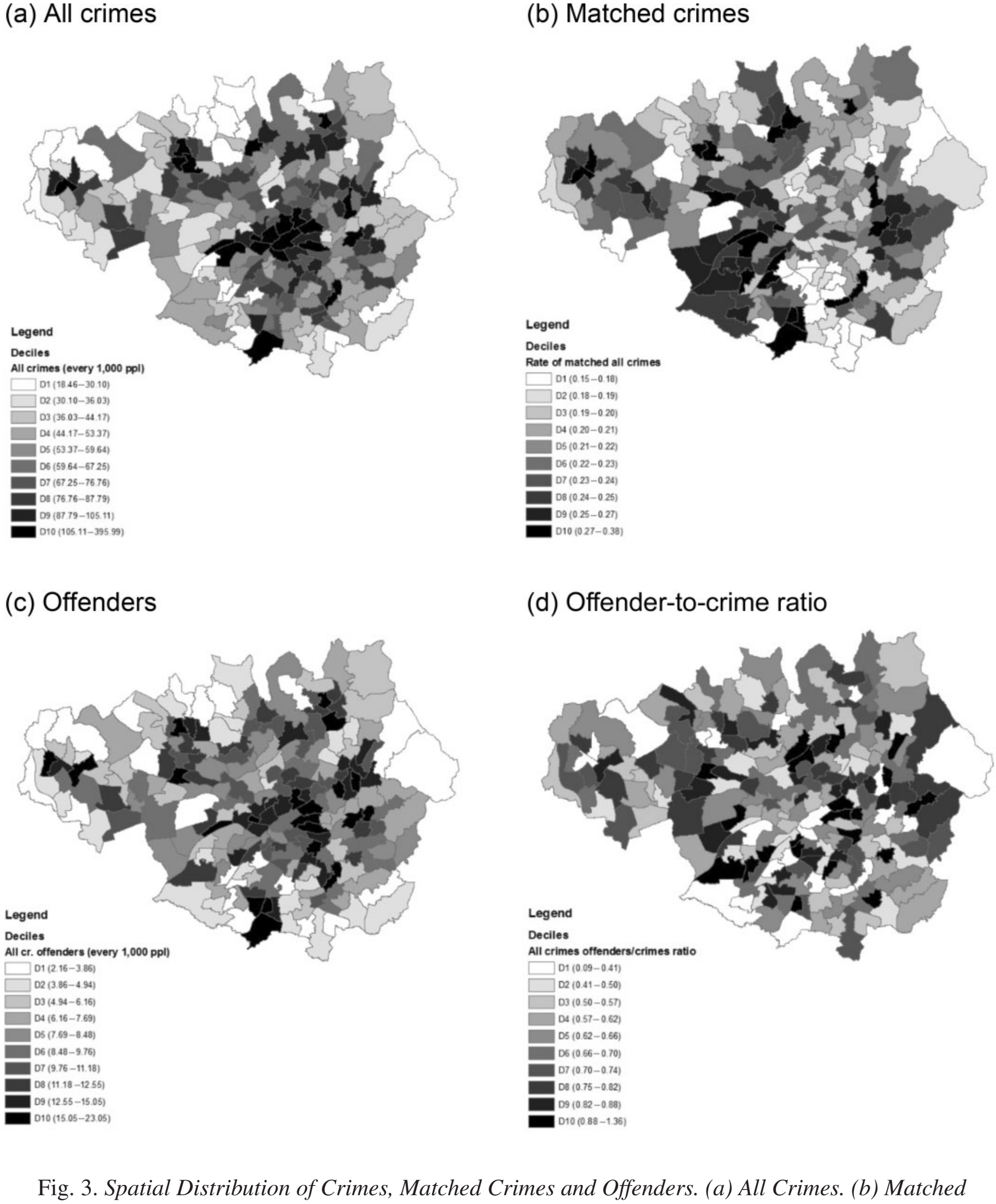

Fig. 3. *Spatial Distribution of Crimes, Matched Crimes and Offenders. (a) All Crimes. (b) Matched Crimes. (c) Offenders. (d) Offender-to-Crime Ratio.*
Source: Authors' elaboration of GMP police force data.

frequent in the Manchester city centre and in some other urban centres. Panel (b) shows a different matched crime distribution; the match rate tends to be higher where crime is less frequent. Panel (c) shows the spatial distribution of the offenders, which also tends to be more concentrated in the Manchester city centre. Finally, panel (d) shows the ratio of offenders to matched crimes by area; this can be thought of as a simple measure of whether an area 'exports' or 'imports' crime.

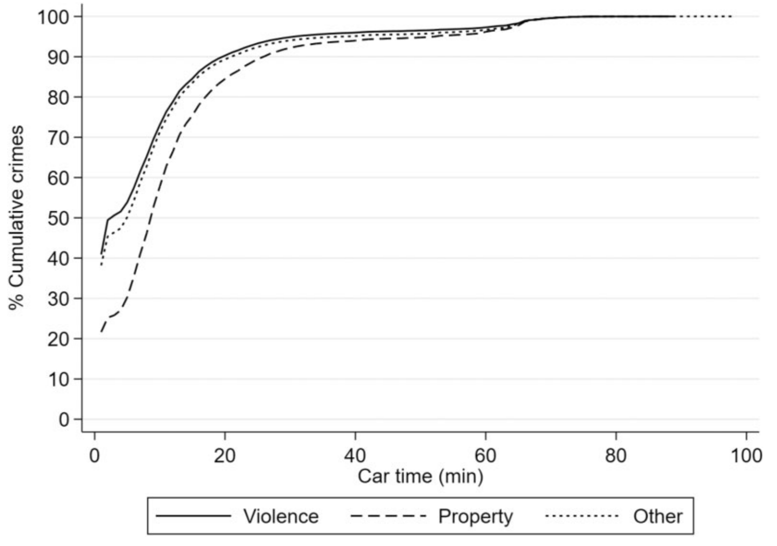

Fig. 4. *The Cumulative Distribution of Distance to Crime, by Crime Type.*
Notes: Distance refers to car time between ward centroids. The cumulative distributions are calculated using all crimes in the whole period of study.

There is considerable variation in the GMP area. Figure A2 in the Online Appendix replicates the same maps separately for the three crime categories: violent, property and other crimes.

Figure 4 shows the cumulative density function of distance from the offender's residence to the crime location measured as car time between the centroids of the offender's and crime's wards. In our main analysis, we use car time as our main measure of distance as 88% of commuters within GMP use a car.[16] Online Appendix Figure A3 shows that the cumulative density function is very similar if we use more precise geo-locations of the offender and crime, so our results are not sensitive to using the distance between ward centroids. Of journeys to crime, 90% are short and are below 20 min of car time. Figure 4 illustrates that journey to crime is slightly longer when we consider property crimes (Rossmo, 2005 pointed out that different types of crime are likely to have different commuting patterns).[17]

2. The Model

2.1. *The Number of Crimes*

Suppose that the number of crimes committed by people from area a (which we refer to as the origin area) in area b (which we refer to as the destination area), $\tilde{N}_{ab}$, is given by the model

$$E(\ln(\tilde{N}_{ab})) = \beta_1 x_a + \beta_2 x_b + \beta_3 x_{ab}, \qquad (1)$$

i.e., it is influenced by some origin area factors x_a, some destination area factors x_b and some factors varying at the origin-destination level x_{ab}, with distance being the most obvious example.

[16] We obtained car and public transport distance (in kilometres) between CAS ward centroids, as well as car and public transport time (in minutes), calculated using average traffic conditions, using HERE technologies.

[17] Online Appendix Figure A4 shows the cumulative density function of distance by detailed type of crime.

One might also distinguish by the type of crime, the date of the crime and the characteristics of the criminal; we omit this to keep notation to a minimum. The Poisson model is the most natural way of estimating this model because there are no matched crimes for many destination-origin pairs.[18]

This type of model can be micro-founded using a discrete-choice model in which an individual criminal is deciding in which of many areas to commit a crime. The discrete-choice model can then be combined with a model for the number of criminals in an area to obtain a model for the total number of crimes. The multinomial logit model (McFadden, 1978)[19] is well known to be equivalent to the Poisson model (Aitkin and Francis, 1992; Baker, 1994; Guimaraes, 2004, among others). Our model also has affinities to other origin-destination models, e.g., gravity models of trade (Overman *et al.*, 2003, among others), commuting for work (Manning and Petrongolo, 2017; Monte *et al.*, 2018; Amior and Manning, 2019) and residential mobility (Langella and Manning, 2022).

However, one difference between our context and these other studies is that we only observe the location of the offender when the offender is caught and recorded. So, the number of *observed* crimes by people living in area a committed in area b will be a function, not just of the number of crimes committed, but also of the probability of being caught. If the probability of being caught is random, this does not affect the estimated model coefficients (apart from the intercept), but, if there is selection correlated with regressors, there needs to be some adjustment for this as commuting for crime estimates would be biased.

Non-random selection seems plausible in our context, as the probability to match a crime-offender pair is likely to be related to distance. The link can be direct if, for example, the police find it easier or harder to solve crimes that involve local offenders. People in the neighbourhood may help in recognising criminals or, in the opposite direction, people might be afraid to collaborate with the police due to the presence of the offender in the neighbourhood. The link can also be indirect if the high-ability or the highly specialised offenders are both less likely to be tracked by the police and may choose where to operate differently from the average offender. We now discuss how we deal with the selection problem.

2.2. *Selection*

Equation (1) cannot be estimated directly because the offender's residence and, hence, distance to crime is not observed for crimes when no offender is found. To correct for this type of selection, we proceed to model the probability of being matched, in a way that builds upon sample selection methods (Wooldridge, 2010, ch.19).

We assume that the probability of an offender being found depends on distance, but also on an instrument z_b, which is a variable observable for all crimes in the sample, which is assumed to affect the probability of an offender being found, but not the number of crimes committed in a specific area:

$$\tilde{F}(\gamma_1 x_{ab} + \gamma_2 z_b). \tag{2}$$

[18] In the full areas $\times$ time matrix, which has 5,495,520 cells, the share of cells with a positive crime count is 1% for violent crimes, and 1.4% for property and other crimes.

[19] See Dahl (2002) and Kennan and Walker (2011), among many others. See Greenwood (1997) for an early review of the literature.

We discuss our choice of instrument later, but, for the moment, we assume that a suitable instrument exists. In the empirical application, the probability of solving a crime is estimated at the individual crime level and the instrument varies at the individual crime level. This individual probability is then aggregated up to give the overall probability for each origin-destination-time observation. However, exposition is easier if we imagine the variation simply being at the area level.

If (2) was known then the expected number of crimes observed committed in area b by people living in area a is the expected number of crimes committed in area b multiplied by the probability of being detected. The number of crimes observed to have been committed by people from a in b can, then, using (1), be written as

$$E(\ln(N_{ab})) = \beta_1 x_a + \beta_2 x_b + \beta_3 x_{ab} + \ln(\tilde{F}(\gamma_1 x_{ab} + \gamma_2 z_b)), \tag{3}$$

where $\tilde{F}$ is the probability that an offender located in a is caught for an offence committed in b. The probability $\tilde{F}$ appears logged in (3) with a unit coefficient, so can be modelled as an offset factor in the Poisson model.[20] If the final term in (3) is omitted, i.e., there is no correction for selection bias, our estimate of the effect of distance on crime will be biased if the probability of a crime being solved is correlated with distance. To correct for any selection bias, we need to control for the final term in (3); however, the problem is that this cannot be directly estimated because the distance is not observed for unmatched crimes.

To solve this problem, we take a first-order Taylor series approximation to $\ln(\tilde{F})$ about the point $E(x_{ab}|x_b, z_b)$. Denoting the value of $\tilde{F}$ at this point by $\widetilde{F_0}$ we can write this approximation as

$$\ln \widetilde{F}(\gamma_1 x_{ab} + \gamma_2 z_b) = \ln \widetilde{F_0} + \frac{\widetilde{F_0}'}{\widetilde{F_0}}[\gamma_1(x_{ab} - E(x_{ab}|x_b, z_b))]. \tag{4}$$

Our approach to dealing with selection bias is to include an empirical version of the right-hand side of (4) as a control function to measure the final term in (3) that, if omitted, is the potential source of bias. This strategy will not work if $\widetilde{F_0}'/\widetilde{F_0}$ is a constant as the control function is then collinear with the distance, the regressor of interest. However, $\tilde{F}$ is a probability, so must be in the unit interval, which means that $\widetilde{F_0}'/\widetilde{F_0}$ cannot be a constant, e.g., it must tend to zero as the probability goes to one. In our application, we use a logit model, in which case, $\widetilde{F_0}'/\widetilde{F_0} = 1 - \widetilde{F_0}$ and, using (4), (3) can be written as

$$E(\ln(N_{ab})) \approx \beta_1 x_a + \beta_2 x_b + \beta_3 x_{ab} + \ln \widetilde{F_0} + (1 - \widetilde{F_0})[\gamma_1(x_{ab} - E(x_{ab}|x_b, z_b))]. \tag{5}$$

Equation (5) involves $\widetilde{F_0}=\tilde{F}(\gamma_1 E(x_{ab}|x_b, z_b) + \gamma_2 z_b)$; this is a function of variables that are observed for all crimes (the location where the crime took place and the instrument) and so can be estimated. Although (5) can be derived from a logit model, it can be given another interpretation. The final term in (5) is the sample selection term; it must be zero when the probability of detection, $\widetilde{F_0}$, is one as selection bias is not possible in this case. It is also plausible that the potential selection bias increases as the probability of detection falls; the simplest functional form to use for this would be linear as in (5). One might think about having higher-order terms in $\widetilde{F_0}$, but may not have the power to identify them. It is also convenient that linearity comes from the commonly used logit model.

[20] Alternatively, one can think of dividing the number of crimes where an offender is found by $\tilde{F}$ and then estimating a Poisson model on this re-scaled number of crimes.

Define

$$F(x_b, z_b) = \tilde{F}(\gamma_1 E(x_{ab}|x_b, z_b) + \gamma_2 z_b) = \widetilde{F}_0. \tag{6}$$

Substituting (6) into (5) we end up with the model we estimate:

$$\begin{aligned} E(\ln(N_{ab})) = \beta_1 x_a + \beta_2 x_b + \beta_3 x_{ab} + \ln(F(x_b, z_b)) \\ + (1 - F(x_b, z_b))[\gamma_1(x_{ab} - E(x_{ab}|x_b, z_b))]. \end{aligned} \tag{7}$$

This is the model we estimate as a Poisson model. The penultimate term in (7), $\ln(F(x_b, z_b))$, is an offset to adjust for variation in the probability of a crime being solved conditional on variables observable for all crimes. The final term in (7) is the interaction of the probability of the crime not being solved, $1 - F(x_b, z_b)$, interacted with the gap between the distance and expected distance. This is the sample selection correction term. The intuition for why this method works is as follows. If there was a value of the instrument for which all crimes were solved, we would have $F(x_b, z_b) = 1$ and the sample selection term would be zero as there is then no selection bias. As the instrument changes and the probability of a crime being solved falls, the extent of sample selection bias will rise and the sample selection term in (7) will also rise. Our approach has affinities to the 'identification at infinity' approach in sample selection models (Chamberlain, 1986).

Before (7) can be estimated we need to have a model for the probability of solving a crime $F(x_b, z_b)$ in terms of variables that can be observed for all crimes, not just those that are solved. To compute the sample selection correction term, we also need an estimate of $E(x_{ab}|x_b, z_b)$. This expectation should be estimated using data for all crimes, not just those where an offender is identified. But we do not observe distance to crime when the crime is not solved. Our approach to this is to weight each crime with an identified offender with one over the probability of that crime being solved, i.e., the inverse of (2). Using the approximation in (4) and taking the exponent of (4) and the logit approximation to the final term in (4) implies that the appropriate weight is given by

$$w = F(x_b, z_b)^{-1} e^{-\gamma_1(1-F(x_b,z_b))[x_{ab}-E(x_{ab}|x_b,z_b)]}. \tag{8}$$

This sets up a conundrum; the control function term in (7) requires an estimate of $E(x_{ab}|x_b, z_b)$. But the estimate of $E(x_{ab}|x_b, z_b)$ requires the weights in (8) that require an estimate of γ_1. But we can only get an estimate of γ_1 from the Poisson regression that uses the control function. The way we solve this conundrum is to use an iterative process with the following steps.

Step 1: Estimate the probability of an offender being found as a function of observables—this gives an estimate of $F(x_b, z_b)$.
Step 2: Initially assume that $\gamma_1 = 0$, i.e., there is no selection bias.
Step 3: Compute weights as in (8) and then estimate a weighted regression of distance on destination and instruments for solved crimes; take the residuals from this distance regression.
Step 4: Estimate the Poisson model (7) using the results from Steps 1 and 3.
Step 5: Take the estimated value of γ_1 go back to Step 3 and repeat until the value of γ_1 is stable.

When this iterative procedure converges, we have found a value of γ_1 that is consistent with the value of the weights used to compute the residuals in the distance regression. It is possible that there is more than one value of γ_1 that satisfies the criteria, but we do not find that the final estimate varies if a different starting value is used in Step 2. We use a tolerance of 1×10^{-10}.[21] We now turn to our results.

3. Results

3.1. *Empirical Specification*

For our empirical implementation, we use wards as our definition of area. There are 214 wards in the GMP area,[22] so we have 214×214 origin-destination cells. We know the exact timing of the crime, so we also add a time dimension to our study. We use the year × month level, which is a balance between using time variation and keeping the sample size manageable. So, for all our estimates, we have a matrix of 214 crime locations × 214 offenders' locations × 120 months, resulting in a dataset of 5,495,520 observations.

Our dependent variable is the count of the number of matched crimes committed in each area by people from every other area. There are many zeroes that are retained in the estimation. We estimate the model separately for each of the three broad crime categories: violent, property and other.

To implement this model, we include time dummies, crime and offender location fixed effects, as well as measures of the distance between each pair of wards. In our main analysis, we use a combination of car time and public transport time to measure distance. Specifically, we include a linear car time term. We also include the ratio of public transport time to car time to capture the idea that some areas that are the same car distance apart may be connected better or worse to the public transport network. There are obviously other distance measures that could be used, but Table A3 in the Online Appendix shows that they are very collinear, perhaps not surprising given we are studying a relatively self-contained urban area.

As explained in Section 2.2, to address selection, we need controls z_b that influence the probability of finding an offender for a given crime, while not directly influencing the number of crimes. We use a broad set of variables reflecting police handling of cases that Blanes i Vidal and Kirchmaier (2018) found to predict whether the crime is solved. First, we use the actual police response time to the crime, constructed as the difference, in minutes, between the time when the case is opened and the time when the police arrive at the crime scene. In addition to the response time, we also include the grade assigned to the incident by the call handler under the GMP Graded Response Policy (Blanes i Vidal and Kirchmaier, 2018), as this reflects intended response times. For example, grade 1 corresponds to events that require immediate response (within 15 min).

One concern about using police response variables as an instrument is that it is possible that the number of crimes committed is affected by the probability of being caught, which might be influenced by the ex ante expected police response time. However, we are using the ex post realised response time that has a lot of idiosyncratic variation depending, for example, on how many police officers are available and where they are at the exact time the crime is committed. Actual and expected response times should be correlated, but we include a rich set of controls to control for the expected response time. We also include destination and origin fixed effects,

[21] In the main analysis and a large part of the robustness checks we used 1×10^{-10} as the level of tolerance. Because of the extended estimation time, we used a lower tolerance in some instances. We specify in the notes to the tables where we applied a tolerance different from 1×10^{-10}.

[22] CAS wards are areas defined according to the 2001 Census of Population. They were initially designed to account for approximately 5,000 people each. Each of the CAS wards in the GMP area accounts for approximately 13,000 people according to the 2011 Census of Population.

which will control for any variation in expected police responses across areas that are fixed over time. Time dummies will instead control for any time variation. To further allay concerns, we provide robustness checks that exclude crimes that are detected directly by the police during patrolling activities, and we show that this does not alter the results. The robustness of results to this sample restriction also allays concerns that some crimes may only be recorded when detected in the act by police.

3.2. *Estimating the Probability of Being Caught*

We estimate the model for the probability of being caught separately for violent, property and other crimes, as in our main analysis we keep these as three separate categories. These models are estimated at the individual crime level and then we aggregate the predicted probability to the origin-destination-month cell level that we use for modelling the number of crimes. There is less variation in the instruments at the cell level than at the individual level, but still sufficient power.

We estimate a logit model where the observations are individual crimes, and the dependent variable is a binary variable for whether an offender was found. The regressors can only relate to the crime and not the offender as the offender is unknown when the crime is unmatched. We include destination and time fixed effects (dummies for the year, month, day of the month, day of the week, hour of the day, day of the week interacted with the month and hour interacted with the day of the week) and the instruments on police response times and priority grading described earlier. We also include dummies for the following crime sub-categories: how the crime was reported to the police, who reported the crime, the type of crime location[23] and a dummy variable for whether the response time is imputed.

Table 3 shows the estimated marginal effects of the logit model for the probability of finding an offender, separately for the different broad crime categories. All variables included are, in general, significant and of the expected sign. As expected, the higher the response time, the lower the probability of matching a crime to an offender. The response time has a slightly smaller influence on the probability of finding an offender for violent crimes than for other crime types.

From these three models, we derive the predicted matching probabilities at the individual crime level. We then aggregate them to the destination × month level to generate $F(x_b, z_b)$ from (6), which is then used to control for selection in the distance cost function model in (7). We now turn to the estimation of this model.

3.3. *The Estimated 'Cost of Distance'*

As for the probability of matching a crime, we separately study violent, property and other crimes. Table 4 shows our main results for the commuting for crime models. Panel A shows the results for models that do not control for selection. As described in Section 3.1, in our main specification we include both car time and a measure of the ratio between public transport time and car time.

For all three crime categories, distance has a large, negative and highly significant estimated impact on the number of crimes, implying that most of the crimes tend to be very local. For

[23] We group this information into six categories: in a house, in a shop or another similar commercial activity, in any other 'indoor' public place (included offices), in any 'outdoor' public place, transportation and a residual category. In addition, a seventh category groups all non-stated types of location.

Table 3. *Logit Models of Selection. Probability of a Crime to be Matched to at Least One Offender. Marginal Effects Displayed (Evaluated at Means).*

	(1) Violent		(2) Property		(3) Other crimes	
Response time (log)—imputed	−0.016***	(0.0005)	−0.007***	(0.0002)	−0.007***	(0.0003)
Response time—dummy for imputed values	−0.053***	(0.003)	−0.062***	(0.002)	−0.083***	(0.002)
Suspect named	0.118***	(0.002)	0.296***	(0.002)	0.189***	(0.001)
Suspect described	−0.094***	(0.002)	−0.080***	(0.001)	−0.058***	(0.001)
Found by the police	0.269***	(0.004)	0.191***	(0.004)	0.269***	(0.003)
Found while patrolling	0.049***	(0.005)	0.017***	(0.003)	0.085***	(0.005)
Reported by the victim	−0.031***	(0.002)	−0.037***	(0.001)	−0.058***	(0.001)
Type of crime:						
Homicide	*Omitted*					
Violence with injury	−0.459***	(0.027)				
Violence without injury	−0.466***	(0.027)				
Other sexual offences	−0.520***	(0.027)				
Rape	−0.566***	(0.027)				
Robbery of business property			*Omitted*			
Robbery of personal property			−0.017***	(0.005)		
Burglary			−0.063***	(0.005)		
All other theft offences			−0.023***	(0.005)		
Vehicle offences			−0.047***	(0.005)		
Theft from the person			−0.054***	(0.005)		
Bicycle theft			−0.037***	(0.005)		
Shoplifting			0.252***	(0.005)		
Criminal damage and arson offences					*Omitted*	
Trafficking of drugs					0.219***	(0.004)
Possession of drugs					0.309***	(0.003)
Possession of weapon offences					0.159***	(0.004)
Miscellaneous crimes against society					0.093***	(0.003)
Public order offences					0.136***	(0.001)
Grade:						
Immediate	0.068***	(0.004)	0.089***	(0.003)	0.141***	(0.003)
Priority	0.028***	(0.003)	0.067***	(0.002)	0.056***	(0.003)
Prompt	−0.015***	(0.004)	0.007***	(0.002)	0.003	(0.176)
Location:						
Home	*Omitted*		*Omitted*		*Omitted*	
Shop	0.035***	(0.003)	0.017***	(0.001)	0.027***	(0.002)
Other closed public/offices	0.097***	(0.003)	0.008***	(0.001)	0.035***	(0.002)
Open air public	−0.018***	(0.002)	0.007***	(0.001)	0.004***	(0.001)
Transportation	0.034***	(0.007)	0.015***	(0.002)	0.023***	(0.004)
Other	0.015***	(0.006)	0.004***	(0.001)	−0.018***	(0.002)
N/A	−0.045***	(0.006)	0.007*	(0.004)	−0.021***	(0.005)
Observations	412,307		996,692		546,590	

Notes: The dependent variable takes the value 1 if the crime is matched to at least one offender, zero otherwise. Robust SEs are reported in parentheses. *** $p < 0.01$, * $p < 0.1$. Constant not reported. Models also include fixed effects for the CAS ward of the crime, year, month, day of the month, day of the week, hour of the day, day of the week interacted with the month and hour interacted with the day of the week. For a description of the control variables, see the notes to Table 1.

instance, for violent crimes, just increasing car time distance by ten minutes—while fixing, in a simplifying exercise, the public transport–car time ratio—reduces the probability of committing a violent crime in that area by approximately 95%. A very similar effect is found for other crimes. Property crimes are slightly less sensitive to distance. The estimates for property crimes show, in fact, that increasing distance by ten minutes brings down the probability of committing a property crime in that area by 'only' 91%.

Table 4. *Poisson Regression Estimates of the Impact of Distance on Crime.*

	(1) Violent crimes	(2) Property crimes	(3) Other crimes
Panel A. Without selection controls			
Car time (minutes)	−0.302***	−0.243***	−0.298***
	(0.006)	(0.006)	(0.005)
Public transport time/car time	−0.447***	−0.194***	−0.379***
	(0.034)	(0.020)	(0.031)
N	5,495,520	5,495,520	5,495,520
Panel B. With selection controls			
Car time (minutes)	−0.247***	−0.172***	−0.251***
	(0.005)	(0.007)	(0.006)
Public transport time/car time	−0.445***	−0.175***	−0.366***
	(0.034)	(0.026)	(0.031)
Sample selection term	−0.101***	−0.148***	−0.163***
	(0.005)	(0.006)	(0.004)
N	5,495,520	5,495,520	5,495,520

Notes: These are estimates of (7). Panel A omits the selection term on the final line and panel B includes it. The dependent variable is the number of matched crimes committed by residents in each ward in every other ward in each month. SEs (in parentheses) are clustered at the destination area level. *** $p < 0.01$. All models include crime location (CAS ward) fixed effects, offender location fixed effects, and year and month fixed effects. The *Sample selection term* is $(1 - F(x_b, z_b))(x_{ab} - E(x_{ab}|x_b, z_b))$.

This is in line with the criminology literature on short journeys to crime, but our results control for unrestricted origin and destination fixed effects, which is not done in other studies and allow us to rule out the possibility that crimes tend to be local simply because criminals and criminal opportunities are located close together.

We also find that, for a given car time, area pairs that are less well connected by public transport have fewer crimes. Doubling the ratio between public transport time and car time reduces the probability of committing a crime by 36% for violent crimes, 18% for property crimes and 32% for other crimes.

The results in Table 4 include car time in linear form. Figure A5 in the Online Appendix investigates alternative functional forms for the impact of car time. Linear car time performs well and has the advantage of being simpler both for estimation and interpretation, so we stick to this specification throughout our paper.

Panel B of Table 4 shows the results for models that include selection controls as outlined by (7). In these models, we control for the estimated probability of finding an offender and an interaction of one minus this probability with the residualised distance, obtained using the convergence procedure described at the end of Section 2.2. Compared to the results of panel A, allowing for sample selection reduces the influence of distance for all crime types. This suggests that the selection bias is going in the direction of overestimating the importance of distance, perhaps because more local crimes are more easily solved. However, distance remains very important. Controlling for selection we find that increasing car time distance by ten minutes—fixing the public transport distance ratio—reduces the probability of committing a crime in a given place by 92% for violent crimes, 83% for property crimes and 93% for other crimes. The impact of the ratio of public transport to car time is similar to what we find without selection controls. Doubling the ratio reduces the probability of committing a crime by 36% for violent crimes, 16% for property crimes and 31% for other crimes.[24]

Overall, our results suggest that controlling for selection is important and tends to reduce the extent to which crime is local and alters the perspective on how close to the offenders' locations different types of crimes are. However, crime does remain very local, with violent and other crimes even more local than property crimes, in line with results obtained in the literature using victimisation data for France (Hémet, 2020).

One interesting question is whether the costs of commuting to crime seem bigger or smaller than the costs of commuting to (legal) work. Online Appendix B estimates a similar model for the number of commuters between the wards of GMP in 2011. We find very similar costs of distance for commuting to work and property crimes. Violent and other crimes are more local.

We next turn to the factors influencing the offender and crime location fixed effects.

3.4. *Local-Level Characteristics Influencing the Crime and Offenders' Locations*

The results reported so far contain offender and crime location fixed effects. The offender location fixed effects contain information on which areas have more offenders, while the crime location area fixed effects contain information on which areas are more attractive as a location for crime. This section relates these estimated fixed effects to the characteristics of the areas. This is useful because it allows us to disentangle the way local conditions influence the number of offenders in an area from the way they affect the crime incidence in the areas. In doing this, we draw on the large body of research that tries to explain the economic drivers of crime. Specifically, we take the estimated fixed effects from panel B of Table 4 and regress them on a set of area characteristics; the results are reported in Table 5.

These fixed effects are very important in explaining the locations of crimes and offenders. For example, for violent crimes, the estimated origin fixed effect has a correlation of 0.43 with the average number of offenders over the whole sample period by ward. The fourth column shows that the estimated origin fixed effect has a correlation of 0.72 with the average number of violent crimes over the whole sample period by ward. Similarly high correlations are observed for the other types of crime. We also present data on cross-correlations; the first column shows that the correlation of the origin fixed effect with the number of violent crimes by area is only 0.09; the distinction between origin and destination matters. The cross-correlation is higher between the destination fixed effect and the number of offenders by area, but still lower than the correlation with the number of crimes. The correlations between the estimated origin and destination fixed effects are 0.18 for violent crimes and 0.04 for property crimes and other crimes, implying that areas with more offenders tend to have more crimes, but the correlation is not very big.

There is large variation in both the origin and destination fixed effect models. For example, the first column shows that the gap between the 90th and 10th percentiles in the estimated origin fixed effects for violent crimes is 1.1; as these come from a Poisson model, one can interpret

[24] To compare the effects of different distance measures, in Online Appendix Table A4 we estimate a double-degree polynomial in each of the distance measures available to us. All models in Table A4 control for selection. For all crime types, the impact of distance is much lower when estimated with public transport time, while it is bigger when estimated with Euclidean distance. Results obtained with physical car and public transport distances are instead very similar to the results with car time. Those models are not directly comparable with our main model, though they provide an interesting comparison among different measures, and some more basis to use a mix of car and public transport times in our analysis, given the different results obtained when using the two separately.

Table 5. *Models for Offender and Crime Location Fixed Effects.*

	Panel A. Offender location			Panel B. Crime location		
	(1) Violent	(2) Property	(3) Other	(4) Violent	(5) Property	(6) Other
Unemployment rate (%)	0.041**	0.060***	0.034*	0.035*	0.046	0.052***
	(0.019)	(0.022)	(0.018)	(0.019)	(0.032)	(0.020)
Population with a degree over 16+ (%)	−0.043***	−0.066***	−0.032***	−0.019	−0.010	−0.030*
	(0.012)	(0.015)	(0.012)	(0.0133)	(0.022)	(0.016)
Population under 15 (%)	0.003	−0.013	0.018	−0.071***	−0.122***	−0.084***
	(0.028)	(0.027)	(0.026)	(0.024)	(0.042)	(0.032)
Population 16–19 (%)	−0.039	−0.051	−0.021	−0.078	−0.027	−0.071
	(0.039)	(0.048)	(0.039)	(0.048)	(0.067)	(0.045)
Population 20–24 (%)	−0.006	−0.024	−0.001	−0.039	0.0001	−0.037
	(0.025)	(0.032)	(0.027)	(0.033)	(0.047)	(0.031)
Population 25–29 (%)	−0.004	0.021	0.011	−0.049	−0.133**	−0.067
	(0.037)	(0.040)	(0.035)	(0.033)	(0.056)	(0.041)
Population 45–64 (%)	−0.006	0.008	0.004	−0.047*	−0.119**	−0.066*
	(0.027)	(0.033)	(0.028)	(0.026)	(0.049)	(0.037)
Population above 65 (%)	−0.031*	−0.043**	−0.024	−0.042**	−0.033	−0.057***
	(0.017)	(0.020)	(0.016)	(0.017)	(0.030)	(0.018)
Married/couples over total population (%)	−0.007	−0.021***	−0.011	0.005	−0.002	0.001
	(0.008)	(0.008)	(0.007)	(0.008)	(0.013)	(0.008)
Students (% of population 16–64)	0.012	0.011	0.008	0.010	−0.055	−0.003
	(0.023)	(0.027)	(0.023)	(0.028)	(0.036)	(0.029)
Population density (standardised)	−0.120***	−0.099***	−0.097***	−0.113***	−0.111*	−0.138***
	(0.032)	(0.038)	(0.035)	(0.033)	(0.061)	(0.037)
Business density (standardised)	−0.092***	−0.053	−0.093***	0.174***	0.219***	0.155***
	(0.025)	(0.033)	(0.027)	(0.025)	(0.039)	(0.024)
People born abroad (% of population)	−0.007	0.005	−0.011	−0.001	0.017	0.021
	(0.009)	(0.012)	(0.008)	(0.011)	(0.018)	(0.013)
Ethnic minorities (%)	0.003	−0.001	0.006	−0.002	−0.0002	−0.013**
	(0.005)	(0.006)	(0.004)	(0.005)	(0.009)	(0.006)
Agriculture and manufacturing (%)	0.001	0.001	0.001	0.002	0.003	−0.001
	(0.002)	(0.003)	(0.003)	(0.003)	(0.004)	(0.003)
Construction/utilities/transportation (%)	0.002	−0.002	0.001	−0.006**	−0.008	−0.005
	(0.003)	(0.004)	(0.003)	(0.003)	(0.006)	(0.003)
Commerce (%)	−0.004*	−0.007**	−0.006**	0.004	0.024***	0.006**
	(0.002)	(0.003)	(0.002)	(0.002)	(0.005)	(0.003)
Hospitality (%)	−0.005	−0.002	−0.003	−0.004	−0.005	−0.005
	(0.003)	(0.004)	(0.003)	(0.004)	(0.005)	(0.004)
Occupation: associate professionals, admin,	−0.020	−0.059***	−0.009	−0.035*	−0.042	−0.055***
skilled trade (%)	(0.016)	(0.019)	(0.016)	(0.018)	(0.028)	(0.020)
Occupation: care, procedural, sales,	−0.043***	−0.061***	−0.032**	−0.001	−0.017	−0.026
elementary (%)	(0.015)	(0.018)	(0.014)	(0.015)	(0.026)	(0.019)
Constant	4.478**	7.232***	3.091	5.002**	8.424*	6.945**
	(2.183)	(2.761)	(2.365)	(2.411)	(4.464)	(2.697)
Observations	214	214	214	214	214	214
Correlation of FEs with the average number of offenders	0.43	0.64	0.36	0.57	0.39	0.54
Correlation of FEs with the average number of offences	0.09	0.10	0.02	0.72	0.63	0.69
SD of dependent variable	0.419	0.601	0.412	0.420	0.657	0.508
$P(10)$ of dependent variable	−0.693	−1.087	−0.717	−0.761	−1.394	−0.948
$P(90)$ of dependent variable	0.417	0.413	0.420	0.252	0.200	0.301
R^2	0.558	0.698	0.533	0.608	0.509	0.597

Notes: The dependent variables in these regressions are the offender and crime location fixed effects from the estimates in panel B of Table 4. Robust SEs are reported in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Models are weighted by population of the ward.

these as the gap in the log expected crimes, implying that the area at the 90th percentile has about three times the number of offenders as the area at the 10th percentile.

Table 5 also reports regressions using the origin and destination fixed effects as dependent variables to investigate the types of areas that have more offenders and more crimes. As regressors, we use 2011 census information about the age distribution of the population, total population, share of married couples, share of foreigners, share of people with a higher education degree, unemployment rate, share of students and the occupational structure of employment. We also include information from the Business Register and Employment Survey, to control for the industrial distribution of the employment in the area. The R^2 of these regressions ranges from 0.36 to 0.72, so, taken together, these factors have considerable explanatory power. These estimates are correlations, not necessarily causal.

Panel A of Table 5 presents the results for the offender location fixed effect. Though it is well known that offenders tend to be young, the age distribution of people in the area is not particularly significant, only the coefficient for population above 65 is negative and significant for all crime types.[25] For all crime types, offenders are less frequent where businesses are denser and population density is higher. Unemployment has a positive relationship with the number of offenders, perhaps because areas with high unemployment have fewer opportunities for work in the labour market. The estimated impact is that a 1 ppt rise in the unemployment rate raises the expected number of violent crimes by 4%, property crimes by 6% and other crimes by 3%. Areas with more university graduates have fewer offenders in their population, especially for property crimes. This is consistent with other studies finding a negative relationship between education and crime (Lochner and Moretti, 2004; Machin *et al.*, 2011; Fella and Gallipoli, 2014; Lochner, 2020).

Panel B of Table 5 presents the results for the crime location fixed effect. These estimates can be interpreted as investigating the area characteristics that make some locations more attractive locations for crime. We find that higher unemployment rates are correlated with more crimes with estimated magnitudes not very different from the impact on the number of offenders. This is different from the findings in some other studies (Cantor and Land, 1985; Freeman, 1999; Gould *et al.*, 2002; Bender and Theodossiou, 2016; Hémet, 2020) and might be thought surprising because low unemployment areas are more attractive locations for property crimes because there is more to steal. However, it may also be the case that there are greater crime prevention measures by richer households (Vollaard and Van Ours, 2011). Areas with higher proportions of the very young and very old are less attractive locations for crimes. Areas with more businesses have more crimes, but those with lower population density have less. We find that areas with a higher fraction of businesses in commerce tend to have more property crimes.

4. Extensions

In the Online Appendix, we report a range of further extensions and results.

4.1. *More Detailed Crime Categories*

Online Appendix Table A5 estimates the model for narrower crime categories. Within property crimes, burglaries and robberies have a lower cost of distance. Within violent crimes,

[25] This is probably because there is insufficient variation in the share of young people across wards to easily identify the impact of age using our methodology.

sexual offences are the more ‘local’ crime category, while looking at other crimes, trafficking and possession of drugs is the crime category with the highest cost of distance. One could summarise this as suggesting that crimes for financial gain seem to have a lower cost of distance.

4.2. *Different Samples of Crimes*

One concern is that some crimes will be solved in the future, but the offender is not observed in our data. Online Appendix Table A6 restricts the sample to crimes where the police have concluded investigations. Online Appendix Table A7 includes only crimes with immediate or prompt response grades. In all cases, results are very similar to the corresponding panels A and B of Table 4. Online Appendix Table A8 shows that results are similar when we restrict the sample to the period until December 2013 where the selection should be slightly less marked, as the crime-offender matching rates were higher. One might be concerned that some crimes are detected by the police themselves, so in Online Appendix Table A9 we exclude from the estimate crimes that are found directly by the police while patrolling or committed at the police station. Also, in this case results are very similar to the main estimates of Table 4.

4.3. *First and Subsequent Offenders*

It is also possible that commuting to crime is different for those who are first offenders as opposed to more career criminals. Figure A6 in the Online Appendix shows that there is some evidence of a mild increasing pattern of distance over the number of crimes committed. For this reason, in Online Appendix Table A10 we re-estimate our model separately for single-time offenders and multiple-time offenders. In Online Appendix Table A11 we instead separate, for multiple-time offenders, the estimate for their first offence and their next offences. There is some evidence that single offenders tend to be more sensitive to distance, and that, for multiple offenders, the sensitivity to distance decreases after the first crime, though the cost of distance remains high and the impact of repeat offending is not particularly large.

4.4. *Interactions of Distance with Area Characteristics*

Online Appendix Table A12 investigates whether the cost of distance varies with the local unemployment and the average level of education in both the offender and crime locations. These variables are chosen because they were significant in our fixed effect regressions. Higher unemployment in the area where a potential offender lives makes the travel to offend shorter both for violent and other crimes. The same applies to areas with a higher incidence of people with a university degree. Higher unemployment at the offender’s location does not seem to have much effect on the estimated cost of distance.

4.5. *Heterogeneities with Respect to Offenders’ Characteristics*

The JtC literature has documented how distance to crime varies with the offenders’ characteristics (Capone and Nichols, 1976; Van Koppen and De Keijser, 1997; Rengert *et al.*, 1999; Carmichael and Ward, 2001; Bernasco and Block, 2009; Townsley and Sidebottom, 2010; Andresen *et al.*, 2014; Ackerman and Rossmo, 2015). To understand whether offenders with different characteristics have different commuting for crime patterns, we re-estimate our distance cost function model on different sub-samples of the offenders' population. Table A13 in the Online Appendix compares the results on the different sub-samples by type of crime.

Age is a characteristic that has been shown to be relevant for distance to crime and our data show similar age-distance patterns to what previous literature finds (Andresen *et al.*, 2014; Ackerman and Rossmo, 2015). Distance increases steeply with age up until the early 20s, while it decreases from the late 20s onwards (Online Appendix Figure A7). We divide the sample into three categories, offenders younger than 25, between 25 and 34 and older than 35, and we estimate our model for the different types of crimes. Columns 1–3 of Online Appendix Table A13 show the results. For all crime types, older offenders tend to be more local, while offenders in the youngest category seem to be willing to travel slightly further to commit a crime. The gradient of the effect across the age groups is increasing for violent and property crimes, while for other crimes, the relation looks a bit more U shaped, though the older category in this case is also the least mobile one.

The other aspect that we compare is gender differences (columns 4 and 5 of Online Appendix Table A13). For all crime types, women are less mobile than men, so more sensitive to distance.

The third aspect that we analyse is differences in terms of the nationality of the offender (columns 6 and 7 of Online Appendix Table A13). For all crimes, offenders of British nationality are willing to travel less than foreigners.

The last aspect we analyse is ethnic identity (columns 8 and 9 of Online Appendix Table A13). For all crime types, white offenders tend to be more sensitive to distance than non-white offenders.

4.6. *Comparison with Traditional Journey-to-Crime Specifications*

Papers in the criminology literature estimate the impact of distance on crime using a different methodology. Typically (as in Ackerman and Rossmo, 2015), this literature estimates a model where the distance to crime is the dependent variable and the regressors include crime and offender characteristics. Compared to our approach, there are several disadvantages. First, while these models tell us about the average distance to crime, they cannot tell us about the number of crimes and how this is affected by distance. In contrast, our approach uses the number of crimes as the dependent variable. Second, there is no simple way to control for the attractiveness of destination areas as targets for crime; typically, the regressors are individual characteristics and origin area characteristics. As emphasised in the introduction, this means that one cannot distinguish between two hypotheses for why most crime is local (the cost of distance is high, or offenders live close to attractive targets). In contrast, our approach is designed to be able to separately estimate the cost of distance and the attractiveness of different areas as targets for crime. Third, this literature does not take into account any bias induced by the selection on crimes with a known offender. There is, however, one advantage to the traditional approach: it is somewhat easier to allow the cost of distance to vary by individual characteristics; this is also possible within our framework, as shown by the results in the previous section.

Given this discussion, it is interesting to compare our results with the more traditional approach; this is done in Table A14 in the Online Appendix where we also discuss similarities and differences from our results.

5. Conclusion

In this paper, we analyse the commuting to crime patterns of offenders in one of the biggest UK urban areas. We use an administrative dataset of the Greater Manchester Police Force that collects detailed information on the locations of crimes as well as the locations of offenders.

We model the number of crimes committed in every neighbourhood by residents of every neighbourhood as a function of the distance between them and crime and offender location fixed effects. This specification allows distinguishing between the roles of commuting costs and offender and crime locations in explaining crime patterns. For example, we can test the hypothesis that most crime is local because offenders and targets for crime are located near each other. We propose a procedure to correct for the possible bias induced by the fact that not all crimes have an offender matched to them. We show that failure to allow for selection leads to an over-estimate of the cost of distance. Nevertheless, crime is very local. After controlling for selection, increasing car time distance by ten minutes reduces the probability of committing a crime in a given place by 92% for violent crimes, 83% for property crimes and 93% for other crimes.

We also model the crime and offender location fixed effects obtained from the distance model as separate functions of the characteristics of these areas such as the age composition, industrial structure and deprivation. We find that area-level characteristics affect crime location and offenders' locations in different ways. Unemployment is positively related to both more offenders and more crimes. The level of education in an area is negatively related to the number of offenders, but has no effect on the number of crimes.

London School of Economics, UK & Copenhagen Business School, Denmark
University of Naples Federico I, Italy & London School of Economics, UK
London School of Economics, UK

Additional Supporting Information may be found in the online version of this article:

Online Appendix
Replication Package

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